REPORT DOCUMENTATION PAGE

AFRL-SR-AR-TR-04-

0174

1. AGENCY USE ONLY (Leave blank)	**2. REPORT DATE** February 23, 2004	**3. REPORT TYPE AND DATES COVERED** Final, Dec 6, 2000-Dec 31, 2003

4. TITLE AND SUBTITLE

Nonlinear Identification and Adaptive Control

5. FUNDING NUMBERS

F49620-01-1-0094

6. AUTHOR(S)

Dennis S. Bernstein

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Aerospace Engineering Department
The University of Michigan
1320 Beal St., Ann Arbor, MI 48109

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Lt. Col. Sharon Heise
Air Force Office of Scientific Research
4015 Wilson Blvd., Rm. 713
Arlington, VA 22203-1954

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

20040324 043

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for public release, distribution unlimited

Approved for public release, distribution unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 Words)*

To address Air Force applications, new methods are developed for system identification (ID) and adaptive control. For linear systems, ID algorithms are developed to obtain consistent parameter estimates, stable models, and optimal inputs. Nonlinear ID methods are developed for block-structured models with measured-input nonlinearities. Subspace ID methods are used to identify linear model components, while optimization methods are used to construct efficient basis functions. Specialized methods are developed to identify nonlinear systems with output nonlinearities, limit cycle dynamics, and hysteresis. Adaptive stabilization algorithms are developed for uncertain linear and nonlinear systems under full-state feedback, as well as linear systems with unknown but bounded relative degree. Extensions to discrete-time systems are addressed. Adaptive command-following algorithms are developed for spacecraft and demonstrated on an experimental testbed. Adaptive disturbance rejection algorithms are developed for tonal and broadband disturbances. Nonlinear control algorithms are developed for shape change actuation for spacecraft. Semistability theory is developed to support research in adaptive control.

14. SUBJECT TERMS system identification, adaptive control, spacecraft control, active Vibration suppression	**15. NUMBER OF PAGES** 22
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	**18. SECURITY CLASSIFICATION OF THIS PAGE**	**19. SECURITY CLASSIFICATION OF ABSTRACT**	**20. LIMITATION OF ABSTRACT**

Nonlinear Identification and Adaptive Control

AFOSR Grant F49620-01-1-0094

Final Performance Report

February 22, 2004

Dennis S. Bernstein
Department of Aerospace Engineering
The University of Michigan
Ann Arbor MI, 48109-2140
Voice: (734) 764-3719
Fax: (734) 763-0578
Email: dsbaero@umich.edu

submitted to

Lt. Col. Sharon Heise
Program Manager, Dynamics and Control
Air Force Office of Scientific Research
AFOSR/NM
4015 Wilson Blvd., Rm. 713
Arlington, VA 22203-1954
Voice: (703) 696-8409
Fax: (703) 696-8450
Email: sharon.heise@afosr.af.mil

1 Abstract

To address Air Force applications, new methods are developed for system identification (ID) and adaptive control. For linear systems, ID algorithms are developed to obtain consistent parameter estimates, stable models, and optimal inputs. Nonlinear ID methods are developed for block-structured models with measured-input nonlinearities. Subspace ID methods are used to identify linear model components, while optimization methods are used to construct efficient basis functions. Specialized methods are developed to identify nonlinear systems with output nonlinearities, limit cycle dynamics, and hysteresis. Adaptive stabilization algorithms are developed for uncertain linear and nonlinear systems under full-state feedback, as well as linear systems with unknown but bounded relative degree. Extensions to discrete-time systems are addressed. Adaptive command-following algorithms are developed for spacecraft and demonstrated on an experimental testbed. Adaptive disturbance rejection algorithms are developed for tonal and broadband disturbances. Nonlinear control algorithms are developed for shape change actuation for spacecraft. Semistability theory is developed to support research in adaptive control.

2 Principal Contributions of the Project

Applications of control-related technology range from "device" scale (for example, precision manufacturing and hard drive control) to "system" scale (for example, UAV technology and the Airborne Laser program). Control technology is a major factor in the success of these applications.

This project addressed a broad range of fundamental issues in control-related technology. Basic research results were obtained in the areas of nonlinear identification and adaptive control. These topics focus on what are, in our view, the core issues in system technology, namely, the construction of models based on empirical data for use in controller synthesis and system prediction, as well as the development of control algorithms that can operate effectively under limited modeling information. These technologies are complementary in the sense that identification is used to provide models that are essential for control, while adaptive algorithms are forgiving to modeling details that are unknowable in advance due to changing conditions.

Our research in this program focused on the development of new methods that have broad application. Rather than apply known methods, our experimental work has motivated and guided the development of new techniques. This approach has been the underlying principle behind 20 years of AFOSR-supported research, leading to more than 150 journal papers, 250 conference papers, 19 graduated Ph.D. students in 12 years, including several employed by DOD laboratories, and numerous additional contributions relating to education, service to the community, and widespread interaction with industry and Government personnel.

For this final report, we summarize our research results, which encompass a diverse collection of problems. First and foremost, our main thrusts in nonlinear identification and adaptive control include new techniques for nonlinear identification of block-structured models as well as adaptive tracking and disturbance rejection. These results are directly applicable to problems of interest to DOD. For example, we have developed novel techniques for non-

linear system identification and applied them to space weather prediction. We have also tested these identification algorithms on fluid flow data. In adaptive control, we extended prior theory on harmonic steady state adaptive control, providing a fully model-free approach that has direct application to precision optical structures under development at AFRL/VS. Additional contributions include a definitive experimental demonstration of the use of shape change actuation for spacecraft attitude control. This idea was adopted by AFRL/VS as a topic for further research in 2003.

As already noted, our program incorporated experimental activities, both computational and physical. We have found control experiments to be invaluable for testing theoretical advances by assessing their performance on real hardware. Accordingly, we have developed several experimental testbeds at the University of Michigan. Several of these testbeds were funded under the DURIP program. We have used these testbeds to develop new ideas, and we have made excellent use of them in our research program [8, 18, 19, 23, 39, 41]

Additional applications include flow control, although such experiments are not available at the University of Michigan. We therefore travelled to the Air Force Academy, where we collected data using the AFOSR-supported Cylinder Wake Benchmark Experiment. We were the first outside group to take advantage of this testbed.

The following sections summarize the principal research results obtained under this project. Details are given in our referenced papers, which are available from standard sources. The reference papers contain numerous references to the related literature.

3 Linear System Identification

Some of the techniques needed for nonlinear system identification are extensions of linear system identification methods. In addition, linear system identification per se is relevant to precision structures applications of relevant to Air Force projects. This project addressed several aspects of linear system identification.

In [33] we developed a variation of least squares identification to guarantee consistency of parameter estimates in the presence of colored process noise. In [27] we applied convex optimization methods to enforce model stability within the context of subspace identification methods. In [21] we developed an optimal-input identification method that selects inputs to minimize error variance as predicted over a finite horizon. Finally, in [17] we developed an identification method that removes the effect of spurious low frequency modes that arise in flexible structure identification.

4 Nonlinear System Identification

While all real systems are nonlinear, the extent to which nonlinearities require modeling is application dependent. In general, the presence of nonlinearities can render linear system identification methods ineffective. Moreover, poor performance of linear system identification methods on real data may be due to either noise, which can be viewed as unmeasured inputs, or hidden nonlinearities. In practice it may be difficult to determine which case is operative without attempting to construct a model of the unmeasured noise signal or the

hidden nonlinearities.

In this project we focused on block-structured models to identify nonlinear subsystem components as separate entities. The ability to visualize these components is useful in applications. The most basic model structures are the Hammerstein, Wiener, and nonlinear feedback models shown in Figure 1, Figure 2, and Figure 3. These models involve the interconnection of a single linear block and a single nonlinear block.

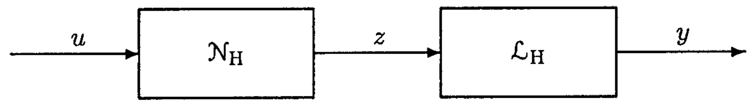

Figure 1: Hammerstein Model

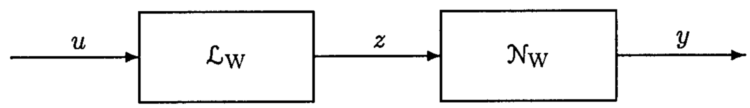

Figure 2: Wiener Model

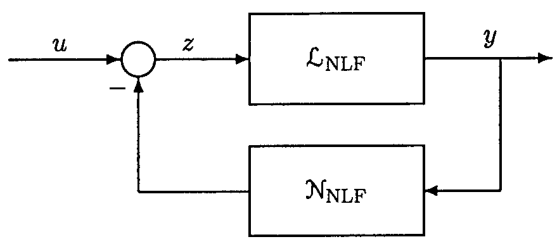

Figure 3: Nonlinear Feedback Model

In [32] we developed a linear spline method to identify Hammerstein and nonlinear feedback models with single-input, single-output nonlinear blocks. Subsequently, we developed a MIMO extension in [22], where a subspace algorithm is used along with a basis expansion for the nonlinear maps. The function expansion is linear in the parameters, which allows the nonlinear system identification problem to be recast as a linear system identification problem with generalized inputs. The multivariable capability of subspace algorithms is central to this approach by allowing an arbitrary number of basis functions.

This approach requires a set of basis functions to represent the nonlinear mapping. We therefore developed techniques in [31] to iteratively refine the basis function representation of nonlinear mappings that are functions of measured inputs. A subspace algorithm is used to identify the linear dynamics for a chosen set of basis functions, while optimization methods are used to refine the set of basis functions. At each iteration, a singular value decomposition of the input matrix is used to identify the dominant nonlinearities. The overall approach can be used with arbitrary basis functions such as polynomials, splines, sigmoids, or Gaussian radial basis. Furthermore, the inputs to the nonlinear mapping can consist of exogenous system inputs as well as outputs that are fed back to the nonlinear mapping.

To illustrate this procedure, consider the nonlinear discrete-time system

$$x_{k+1} = Ax_k + F(u_k, y_k), \tag{4.1}$$

$$y_k = Cx_k + G(u_k), \tag{4.2}$$

where $x_k \in \mathbb{R}^n$, $u_k \in \mathbb{R}^m$, $y_k \in \mathbb{R}^p$, $A \in \mathbb{R}^{n\times n}$, $C \in \mathbb{R}^{p\times n}$, $F\colon\ \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}^n$, and $G\colon\ \mathbb{R}^m \to \mathbb{R}^p$. The functions F and G can be written in terms of their scalar-valued components as

$$F(u,y) = \begin{bmatrix} F_1(u,y) \\ \vdots \\ F_n(u,y) \end{bmatrix}, \quad G(u) = \begin{bmatrix} G_1(u) \\ \vdots \\ G_p(u) \end{bmatrix}, \tag{4.3}$$

where, for all $i = 1,\ldots,n$, $F_i\colon\ \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$ and, for all $i = 1,\ldots,p$, $G_i\colon\ \mathbb{R}^m \to \mathbb{R}$. By defining

$$z \triangleq \mathcal{N}(u,y) \triangleq \begin{bmatrix} F(u,y) \\ G(u) \end{bmatrix}, \tag{4.4}$$

the system (4.1), (4.2) can be illustrated as in Figure 4, where $\mathcal{N}\colon\ \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}^{n+p}$ and $\mathcal{L}$ represents the linear system

$$x_{k+1} = Ax_k + \begin{bmatrix} I_n & 0 \end{bmatrix} z_k, \tag{4.5}$$

$$y_k = Cx_k + \begin{bmatrix} 0 & I_p \end{bmatrix} z_k, \tag{4.6}$$

where $z_k \triangleq \mathcal{N}(u_k, y_k)$ is viewed as an unmeasured, exogenous input to $\mathcal{L}$.

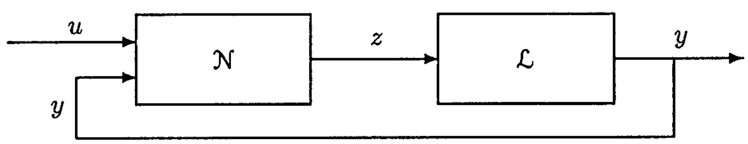

Figure 4: Nonlinear system with measured-input nonlinearities.

The main feature of the model (4.5), (4.6) is the fact that all of the inputs to $\mathcal{N}$ are measured. Therefore, the model (4.1), (4.2) includes the Hammerstein and nonlinear feedback models shown in Figure 1 and Figure 3. However, (4.1), (4.2) does not encompass the Wiener model shown in Figure 2.

Next, assume that the components F_i and G_i can be expanded in terms of basis functions $f_1(u,y),\ldots,f_q(u,y)$, $g_1(u),\ldots,g_r(u)$, and $h_1(u),\ldots,h_s(u)$ as

$$F(u,y) = \begin{bmatrix} \sum_{i=1}^q b_{f1i} f_i(u,y) + \sum_{i=1}^s b_{h1i} h_i(u) \\ \vdots \\ \sum_{i=1}^q b_{fni} f_i(u,y) + \sum_{i=1}^s b_{hni} h_i(u) \end{bmatrix}, \tag{4.7}$$

$$G(u) = \begin{bmatrix} \sum_{i=1}^r d_{g1i} g_i(u) + \sum_{i=1}^s d_{h1i} h_i(u) \\ \vdots \\ \sum_{i=1}^r d_{gpi} g_i(u) + \sum_{i=1}^s d_{hpi} h_i(u) \end{bmatrix}. \tag{4.8}$$

The functions h_i are the basis functions that are common to both F and G. Defining $f\colon\ \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}^q$, $g\colon\ \mathbb{R}^m \to \mathbb{R}^r$ and $h\colon\ \mathbb{R}^m \to \mathbb{R}^s$ by

$$f(u,y) = \begin{bmatrix} f_1(u,y) \\ \vdots \\ f_q(u,y) \end{bmatrix}, \quad g(u) = \begin{bmatrix} g_1(u) \\ \vdots \\ g_r(u) \end{bmatrix}, \quad h(u) = \begin{bmatrix} h_1(u) \\ \vdots \\ h_s(u) \end{bmatrix}, \tag{4.9}$$

it follows from (4.8) that

$$F(u,y) = B_f f(u,y) + B_h h(u), \quad G(u) = D_g g(u) + D_h h(u), \tag{4.10}$$

where $B_f \triangleq [b_{fij}] \in \mathbb{R}^{n\times q}$, $B_h \triangleq [b_{hij}] \in \mathbb{R}^{n\times s}$, $D_g \triangleq [d_{gij}] \in \mathbb{R}^{p\times r}$, and $D_h \triangleq [d_{hij}] \in \mathbb{R}^{p\times s}$. Thus (4.1), (4.2) can be written as

$$x_{k+1} = Ax_k + B_f f(u_k, y_k) + B_h h(u_k), \tag{4.11}$$
$$y_k = Cx_k + D_g g(u_k) + D_h h(u_k), \tag{4.12}$$

or more compactly as

$$x_{k+1} = Ax_k + B \begin{bmatrix} f(u_k, y_k) \\ g(u_k) \\ h(u_k) \end{bmatrix}, \tag{4.13}$$

$$y_k = Cx_k + D \begin{bmatrix} f(u_k, y_k) \\ g(u_k) \\ h(u_k) \end{bmatrix}, \tag{4.14}$$

where

$$B \triangleq \begin{bmatrix} B_f & 0 & B_h \end{bmatrix}, \quad D \triangleq \begin{bmatrix} 0 & D_g & D_h \end{bmatrix}. \tag{4.15}$$

As a special case of the system shown in Figure 4, consider the Hammerstein system

$$x_{k+1} = Ax_k + F(u_k), \tag{4.16}$$
$$y_k = Cx_k + G(u_k), \tag{4.17}$$

where now the function F depends only on the input u. In the case that F and G are represented by a common set of basis function $h_1, \ldots, h_s$, it follows that

$$\begin{bmatrix} F(u) \\ G(u) \end{bmatrix} = \begin{bmatrix} B \\ D \end{bmatrix} h(u), \tag{4.18}$$

(4.19)

where $B = B_h \in \mathbb{R}^{n\times s}$ and $D = D_h \in \mathbb{R}^{p\times s}$. Hence (4.16), (4.17) become

$$x_{k+1} = Ax_k + Bh(u_k), \tag{4.20}$$
$$y_k = Cx_k + Dh(u_k). \tag{4.21}$$

The nonlinear system identification problem is to construct models of both $\mathcal{L}$ and $\mathcal{N}$ given measurements of (u_k, y_k) over the interval $0 \le k \le \ell$. The signal z is assumed to be unavailable.

The next step is to refine the representation of the nonlinear subsystem blocks. We illustrate the procedure for the Hammerstein case (4.20), (4.21). To begin, consider an initial set of basis functions $\hat{h}_1, \ldots \hat{h}_{\hat{s}}$ with $\hat{h} \triangleq [\ \hat{h}_1 \ \cdots \ \hat{h}_{\hat{s}}\ ]^{\mathrm{T}}$ and let $(\hat{A}, \hat{B}, \hat{C}, \hat{D})$ denote an estimate of (A, B, C, D) provided by the subspace algorithm. Next, consider the singular value decomposition of $\left[\begin{smallmatrix} \hat{B} \\ \hat{D} \end{smallmatrix}\right]$ written in standard notation as

$$\begin{bmatrix} \hat{B} \\ \hat{D} \end{bmatrix} = \hat{U}\hat{\Sigma}\hat{V}. \tag{4.22}$$

Then, we retain the largest ν singular values in $\hat{\Sigma}$ to obtain the approximation $\hat{\Sigma} \approx \hat{\Sigma}_0 = \hat{L}_0\hat{R}_0$, where $\operatorname{rank}\hat{\Sigma}_0 = \nu$ and the matrices $\hat{L}_0 \in \mathbb{R}^{(n+p)\times\nu}$ and $\hat{R}_0 \in \mathbb{R}^{\nu\times s}$ have full column rank and full row rank, respectively. The retained ν largest singular values can be incorporated into either $\hat{L}_0$ or $\hat{R}_0$. This yields the approximation

$$\begin{bmatrix} \hat{B} \\ \hat{D} \end{bmatrix} \hat{h}(u) = \hat{U}\hat{\Sigma}\hat{V}\hat{h}(u) \approx \hat{U}\hat{\Sigma}_0\hat{V}\hat{h}(u) = \hat{U}\hat{L}_0\hat{R}_0\hat{V}\hat{h}(u) = \begin{bmatrix} \hat{B}_0 \\ \hat{D}_0 \end{bmatrix} \hat{h}_0(u), \tag{4.23}$$

where the matrix $\left[\begin{smallmatrix} \hat{B}_0 \\ \hat{D}_0 \end{smallmatrix}\right] \triangleq \hat{U}\hat{L}_0 \in \mathbb{R}^{(n+p)\times\nu}$ and $\hat{h}_0(u) \triangleq \hat{R}_0\hat{V}\hat{h}(u)$ satisfying $\hat{h}_0\colon\ \mathbb{R}^m \to \mathbb{R}^\nu$ is a column vector consisting of ν scalar-valued nonlinear functions. The motivation for this procedure is to retain only ν scalar-valued nonlinear functions each of which is a linear combination of $\hat{s}$ basis functions. Since $\nu << \hat{s}$, the ν scalar-valued components of $\hat{h}_0$ can be viewed as dominant nonlinearities, while the choice of ν reflects the rank of the nonlinear mapping $\left[\begin{smallmatrix} F \\ G \end{smallmatrix}\right]$.

With the basis functions $f_i(u, y), g_i(u), h_i(u)$ specified, subspace algorithms can be applied to the system (4.5), (4.6) with the signal z playing the role of the exogenous input. This is the approach developed in [22]. The type of basis functions chosen (for example, polynomial, spline, or radial basis functions) will, in general, affect the number of basis functions needed to achieve a satisfactory approximation of the nonlinear mappings in a particular application. While subspace identification yields the coefficient matrices (A, B, C, D), it does not determine the basis functions. Consequently, in [31] we extended this nonlinear identification approach to include the ability to optimize over a class of basis functions. For example, if Gaussian radial basis functions are used, then these functions can be optimized with respect to the center location and half-width.

We address this problem in [31] by optimizing the fit error with respect to the parameters that characterize the basis functions. For example, for the case of Gaussian radial basis functions, gradient expressions with respect to the center locations and half-widths are derived, and numerical optimization alternately with subspace identification to determine both the linear model and basis functions to minimize the fit error. A less computationally intensive procedure is to choose random basis functions, which are retained or discarded based on their effectiveness in reducing the fit error.

To illustrate the nonlinear identification algorithm for nonlinear system identification, we consider a data set used for space weather prediction. The input data set was measured by the NASA Advanced Composition Explorer (ACE) spacecraft and includes the three components of the magnetic field vector as well as the solar wind speed, solar wind proton density, and temperature. The system output is the cross polar cap potential, which is derived from 85 magnetometers located in Greenland, Canada, Scandinavia, Alaska, and Russia.

For the data fit shown in Figure 5, 3 of the 7 inputs (the solar wind speed and two components of the magnetic field) are used to construct a rank 2 input nonlinearity, that is, a Hammerstein system with two dominant nonlinearities. The final rank 2 input nonlinearity is a combination of 135 radial basis functions. The linear dynamics identified by the subspace algorithm are second order.

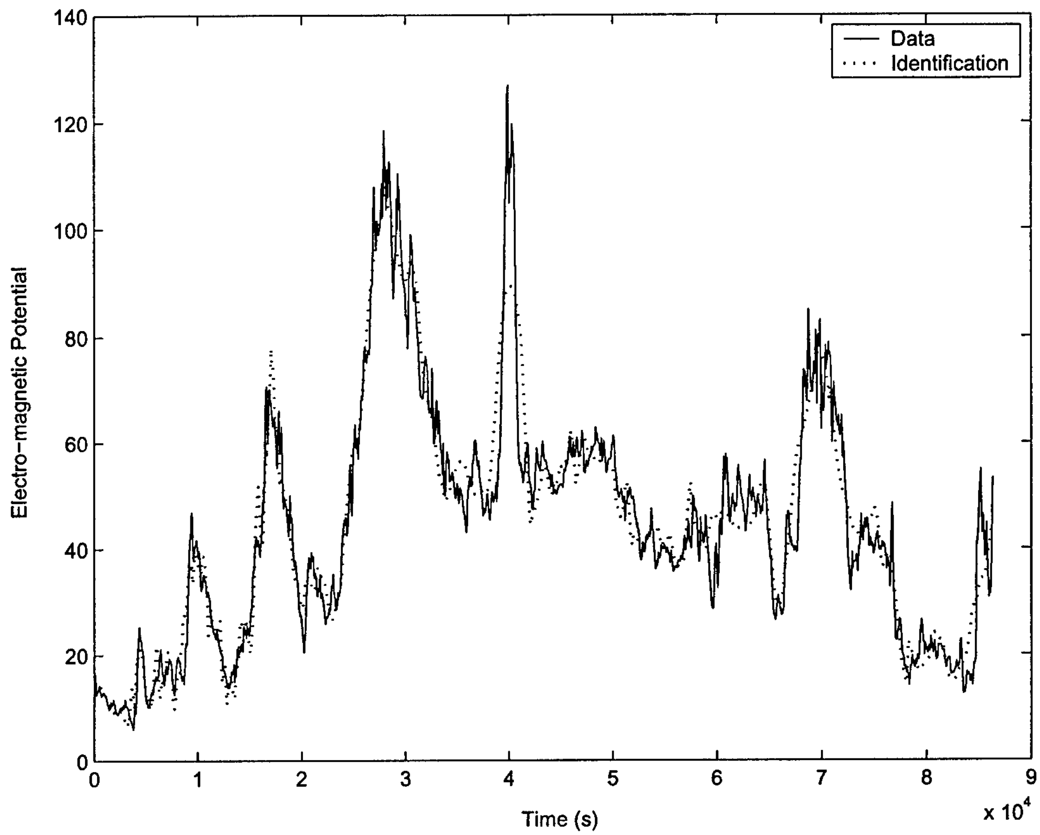

Figure 5: Data fit for space weather system with three inputs and one dominant nonlinearity represented by 135 radial basis functions.

As a second example, we consider experimental data obtained for the NASA Dryden Aerostructures Test Wing (ATW), mounted on an F-15 to provide a flying wind tunnel. The data used for identification are obtained from a test performed at Mach number 0.80 and altitude 20,000 ft.

The identification input is a 5 to 35 Hz sine sweep applied to piezoelectric patches on the ATW. The output is the acceleration of the ATW boom at mid-length. A total of 60 sec of recorded data is available, of which 2 sec of data are used for nonlinear system identification. The identified model is 5th-order with a rank 1 input nonlinearity. For initialization, 15 evenly spaced radial basis functions are used for the first iteration. For visualization purposes, Figure 6 shows 1 sec of data fit, and the identified dominant nonlinearity is shown in Figure 7. These methods were also applied to laboratory data obtained from testing linear motors in [24].

As an additional application of this nonlinear identification method, we participated in

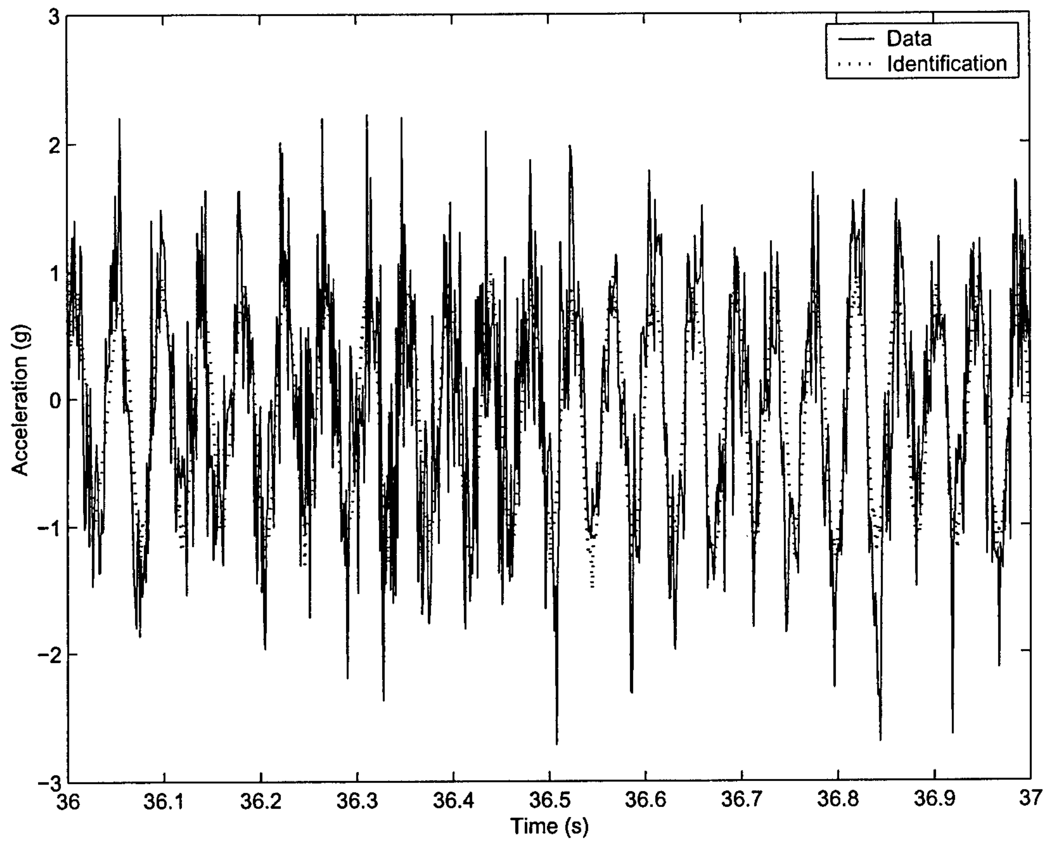

Figure 6: Data fit for test wing with piezo sine sweep forcing under constant aerodynamic conditions.

the AFOSR-supported Cylinder Wake Benchmark Experiment developed at the Air Force Academy. This flow control experiment is set in a water tunnel with PIV flow sensing. Nominal operation is at a Reynolds number of 120 and a natural vortex shedding frequency of 1.2 Hz. The controller sampling rate is 30 Hz with 70 ms time delay due to PIV processing and data transfer, which corresponds to 10% of the natural vortex shedding frequency. The objective of the testbed is to use feedback control to reduce drag on a cylinder that can be moved in a vertical plane. The experiment has been designed to allow outside researchers to test control methods. Control software is implemented on a dSPACE system that is identical to systems at the University of Michigan.

For the Cylinder Wake Benchmark Experiment, Dr. Stefan Siegel has made available 2D CFD simulation data for the velocity field downstream from the cylinder for both harmonic and chirp cylinder motion. CFD simulation is performed using the Cobalt, Inc., Navier-Stokes flow solver with an interface to Matlab for sensing, actuation, and controller implementation. Numerical results obtained under harmonic cylinder motion at the natural vortex shedding frequency show sinusoidal velocity response. For chirp cylinder motion, the velocity response is more complex.

For the chirp cylinder data, we applied the selective refinement nonlinear system identifi-

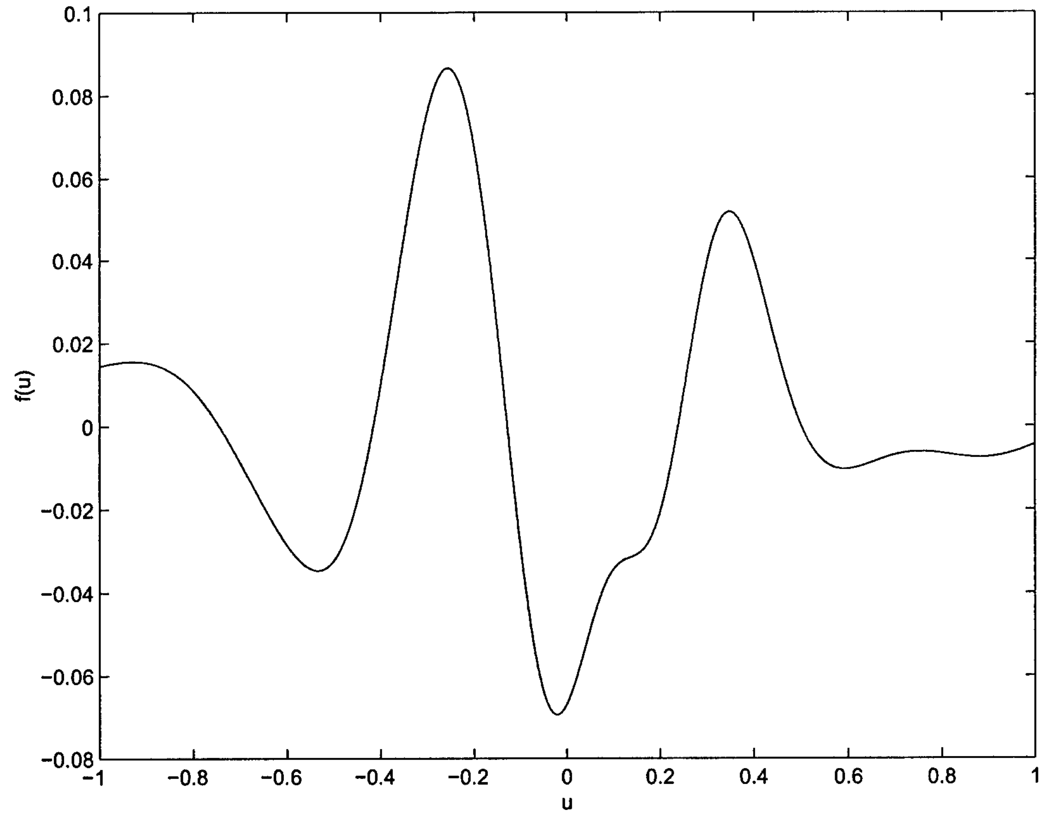

Figure 7: Dominant identified input nonlinearity for the Dryden test wing with piezo forcing using a 5th-order Hammerstein model and a rank 1 nonlinearity.

cation algorithm to obtain a model that fits both components of the velocity. A total of 400 time steps of CFD data were provided for the case of chirp signal cylinder displacement. The data fit for the x velocity component at a point downstream is shown in Figure 8, while the identified nonlinearity is shown in Figure 9. The identification data fit was found by choosing an initialization of 11 radial basis functions, and the subspace identification algorithm identified a 9th-order linear system. Although spanwise modes are assumed to be excited by this motion, 3D CFD data are not available.

The block-structured nonlinear models identified by the methods described above can be used in nonlinear control design. We considered nonlinear control of Hammerstein systems for applications involving electromagnetic actuation in [36].

The methods discussed above are limited to nonlinear systems whose nonlinear maps have measured inputs. Models of interest that do not satisfy this assumption include Wiener systems whose output map may not be one-to-one. Partial results on this problem include the case of a known, non-invertible (that is, not one-to-one) output mapping [28] as well as the case of an unknown, non-invertible output mapping with the linear dynamical system assumed to be finite impulse response [25]. The interesting feature of these systems is the fact that they appear to be identifiable despite the ambiguity in their output maps.

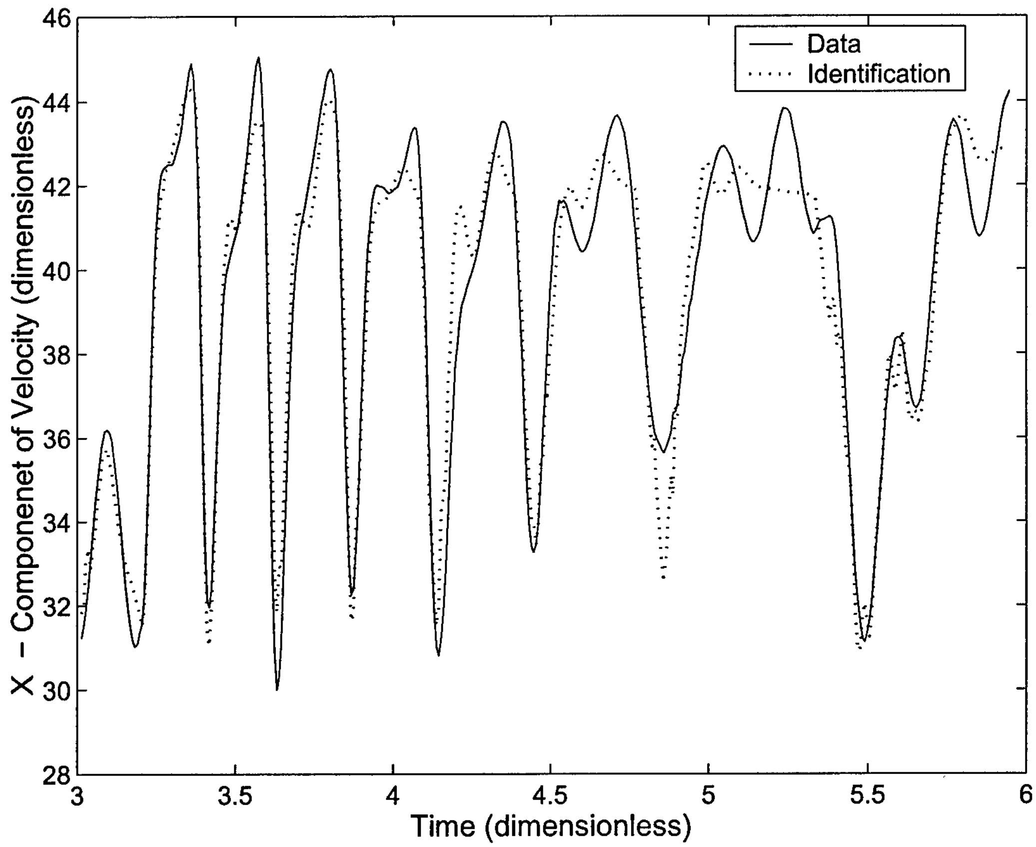

Figure 8: x-direction data fit for Cylinder Wake Benchmark Experiment using a 9th-order model and a rank 1 input nonlinearity.

As a special class of nonlinear system identification problems, we also considered the identification of systems with limit cycles. Systems with limit cycles are self oscillating, that is, they have the property that constant inputs produce periodic outputs. Applications include aerodynamic instabilities (surge and stall), aeroelastic instabilities (flutter), thermoacoustic instabilities (combustion), contact instabilities (chatter, squeal), rotating instabilities (unbalanced rotors and linkages), and hysteresis (relays, backlash). The results given in [26] are based on techniques that are closely related to the reconstruction and restoration methods developed in the dynamical systems literature.

Finally, we developed nonlinear identification methods for a class of systems that model hysteresis. The semilinear Duhem model provides a finite-dimensional model that can capture both rate-independent and rate-dependent hysteresis effects. The semilinear Duhem model was analyzed in [29], and nonlinear identification methods were demonstrated in [29, 30].

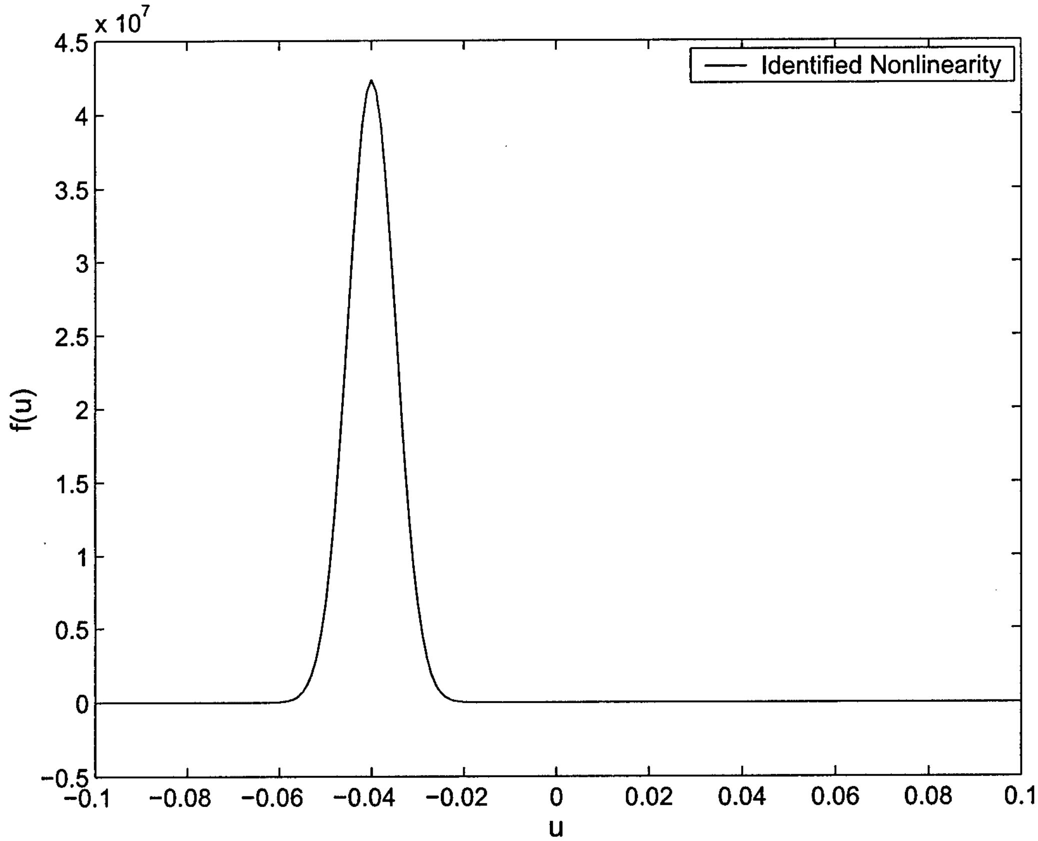

Figure 9: Dominant identified nonlinearity for Cylinder Wake Benchmark Experiment.

5 Adaptive Control

Our research in adaptive control encompasses adaptive stabilization, adaptive command following, and adaptive disturbance rejection. In adaptive stabilization and command following, noise and disturbance signals are usually not considered. In adaptive disturbance rejection, the plant is usually assumed to be open-loop stable, and the key objective is to reduce the effect of disturbances.

The goal of adaptive stabilization is to devise a controller that can stabilize the plant under limited modeling information and through continual gain adjustment. Our earliest work on this topic was [20], which provided an accessible introduction to the basic ideas. We subsequently showed that this controller is effective for certain classes of nonlinear and time-varying systems [34, 35]. Additional results include adaptive stabilization of linear systems with unknown but bounded relative degree as considered in [16].

For spacecraft applications we developed an adaptive command-following controller in [2] for spacecraft with unknown mass distribution (including unknown moments of inertia and center of mass), and we developed similar controllers for a dual-gimbal control-moment gyro and a rigid rotor, which was implemented on an experimental testbed [1]. More recently [38],

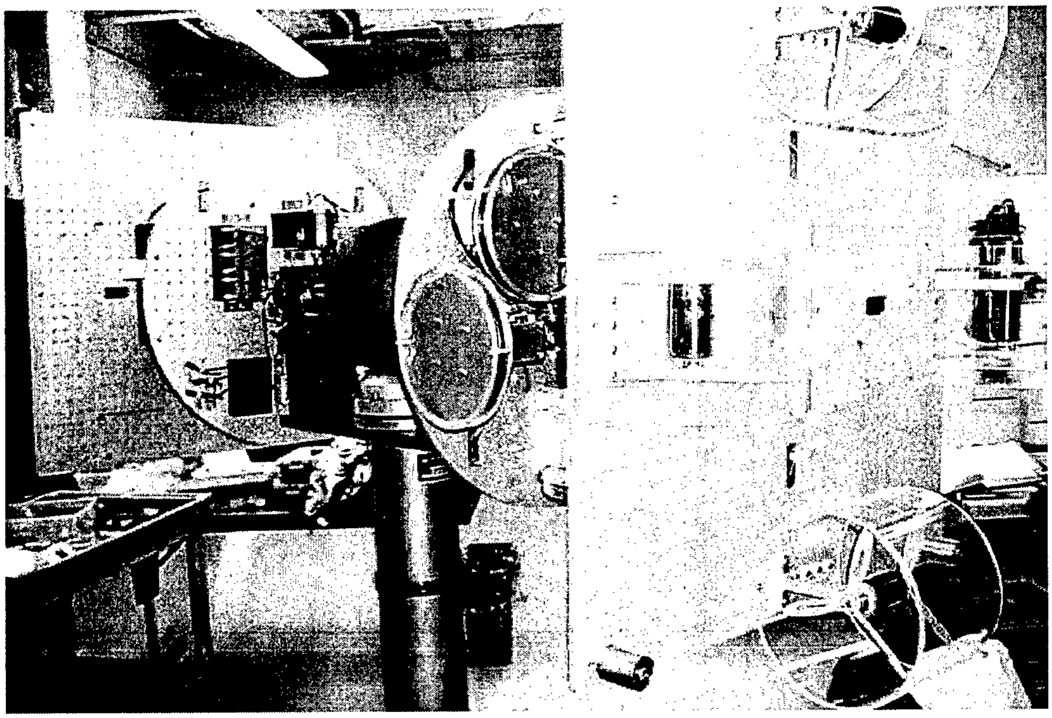

Figure 10: Triaxial testbed. This 3D attitude control testbed uses a low-friction triaxial air bearing to emulate three-dimensional rotational dynamics. Reaction wheels and fan thrusters are used for actuation. Inertial sensors and magnetometers are used for attitude estimation.

we applied a related approach to an experimental testbed that simulates spacecraft motion in up to 3 degrees of freedom (see Figure 10). For this testbed, torque inputs are realized by fans, which possess nonlinearity that degrades the tracking performance and inertia estimates. For this system, which is a Hammerstein system with unknown input nonlinearity, the adaptive control law lacks robustness to harmonic commands. Therefore, we implemented adaptive feedback linearization in [37] to adaptively invert the input nonlinearity in conjunction with inertia identification.

For digital implementation, we explored these problems in a discrete-time setting. First, we considered adaptive stabilization with both quadratic and logarithmic Lyapunov functions [4, 44]. We showed in [5] that discrete-time adaptive control laws require normalized gain updates, which can be shown to be Lyapunov stable using logarithmic Lyapunov functions. Logarithmic Lyapunov functions were also applied to the problem of discrete-time model reference adaptive control in [3], where Lyapunov stability was shown.

The problem of adaptive disturbance rejection generally assumes that the plant is open-loop stable, and seeks to suppress disturbances under minimal plant and disturbance modeling. For this problem it is important to make a distinction between tonal (sum of sinusoids) and broadband disturbances. For tonal disturbances that are not measured, the classical approach to disturbance rejection is to use a controller that includes a model of the exogenous

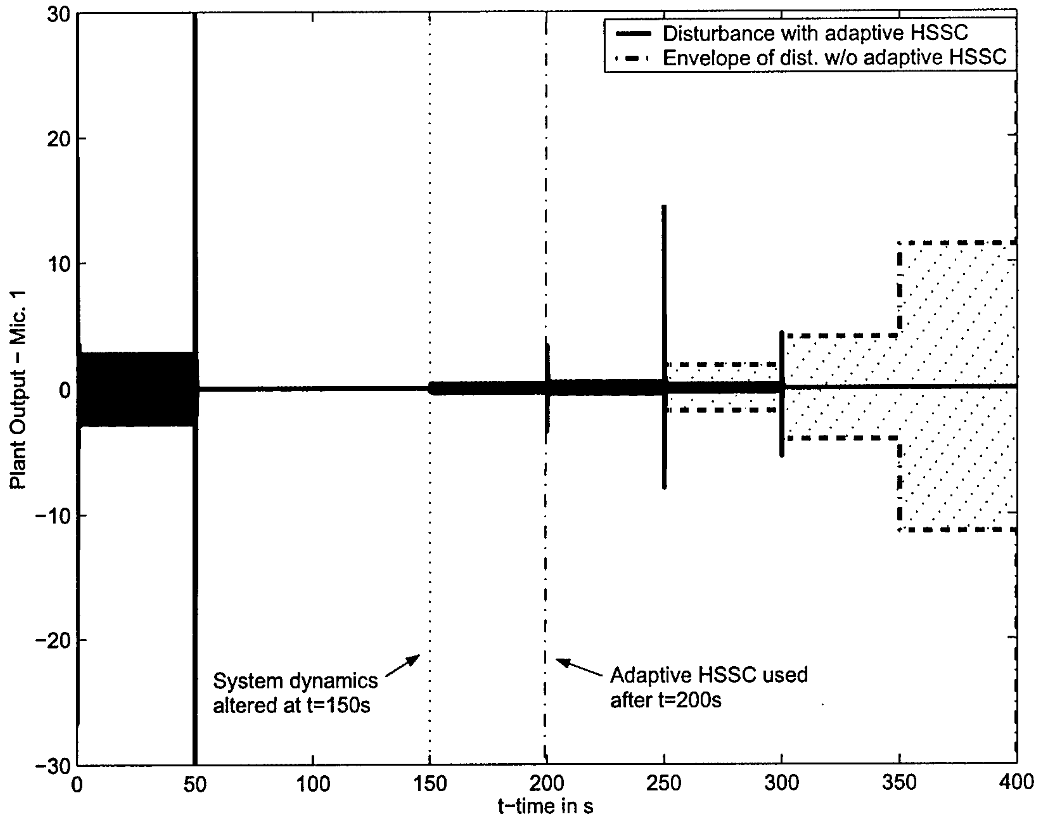

Figure 11: Experimental application of harmonic steady state adaptive control. This algorithm uses a recursive least squares estimator to obtain a completely model-free disturbance rejection algorithm for tonal disturbances.

disturbance in accordance with the internal model principle. Internal-model-based control has the useful property that neither the amplitude nor the phase of the disturbance need be known for asymptotic disturbance rejection. However, in order to implement an internal model controller, some plant modeling information is needed to ensure stability. In fact, it can be shown that, with sufficiently small feedback gains, closed-loop stabilization requires knowledge of the sign of the imaginary part of the plant frequency response at the disturbance frequency. An additional difficulty arises when the frequency of the disturbance is not known. In this case, an adaptive controller is needed, and a globally convergent algorithm for this problem (even in the presence of a fully modeled plant) remains open.

To address this problem, we considered the approach of harmonic steady state control, which is closely related to higher harmonic control applied to rotorcraft vibrations. In this approach, the disturbance is assumed to be tonal, and the system is allowed to reach harmonic steady state. In [14] we extended existing methods to include a concurrent identification algorithm. The resulting algorithm is fully adaptive and model free. Experimental results obtained for an acoustic testbed are shown in Figure 11.

In prior research, we developed the ARMarkov adaptive cancellation algorithm [42, 43]. In

this approach, controller synthesis is based on ARMarkov models and thus Markov parameters. The ARMarkov adaptive disturbance rejection algorithm requires no prior knowledge of the disturbance spectrum and minimal modeling of the plant dynamics. Specifically, a model of the transfer function G_{zu} from control to performance is required, while no knowledge of the remaining transfer functions G_{zw}, G_{yw}, G_{yu} (from control to measurement, disturbance to performance, and disturbance to measurement) is needed. None of these transfer functions is assumed to be positive real, and the algorithm does not require accessibility of either the disturbance signal or the full state.

In laboratory experiments, we have applied the ARMarkov adaptive control algorithm to noise and vibration control testbeds with both stationary and nonstationary disturbances, including single tones, multiple tones, white noise, and sine sweeps. In these experiments the controller has no prior knowledge of the nature of the disturbance, and only the (MIMO) transfer function G_{zu} from control inputs to performance variables is identified in advance. Figures 12 and 13 show experimental results for dual-tone and white noise disturbances after controller convergence. The algorithm has also been applied to a structural vibration experiment shown in Figure 14 involving membrane dynamics [18].

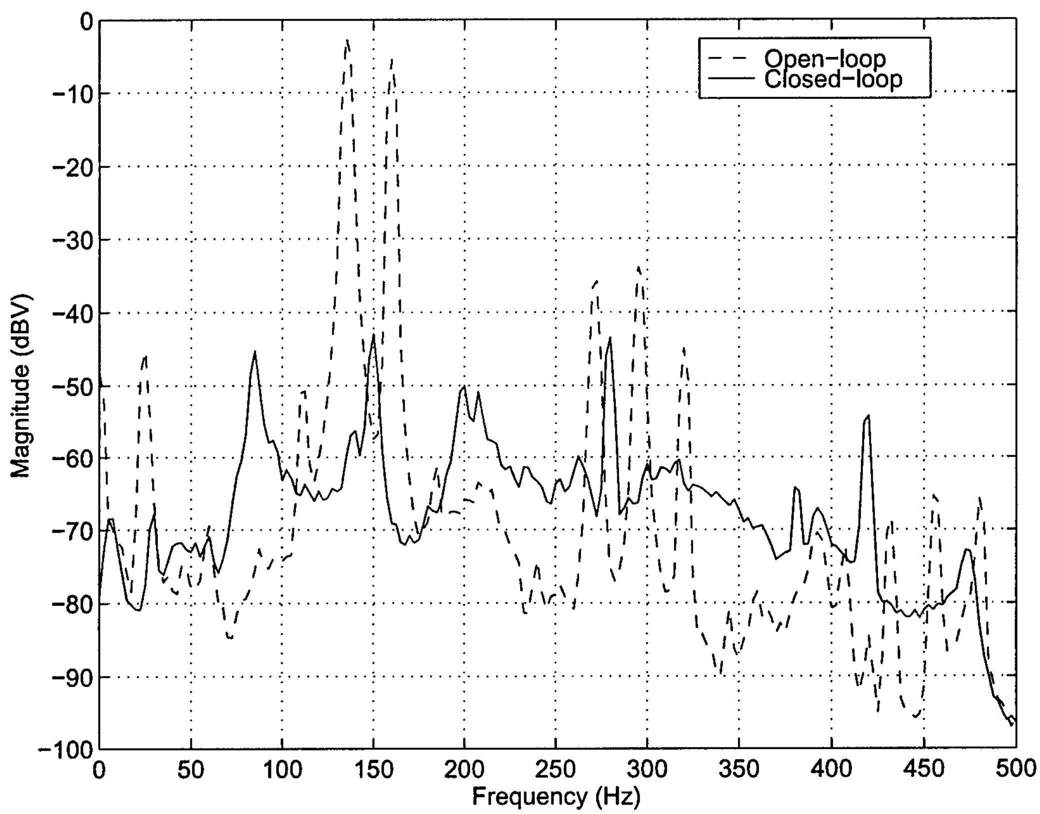

Figure 12: This frequency response plot compares the open- and closed-loop performance of the ARMarkov adaptive control algorithm with dual-tone disturbance. The adaptive control algorithm has knowledge of only the zeros of the transfer function G_{zu} and has no knowledge of the disturbance spectrum.

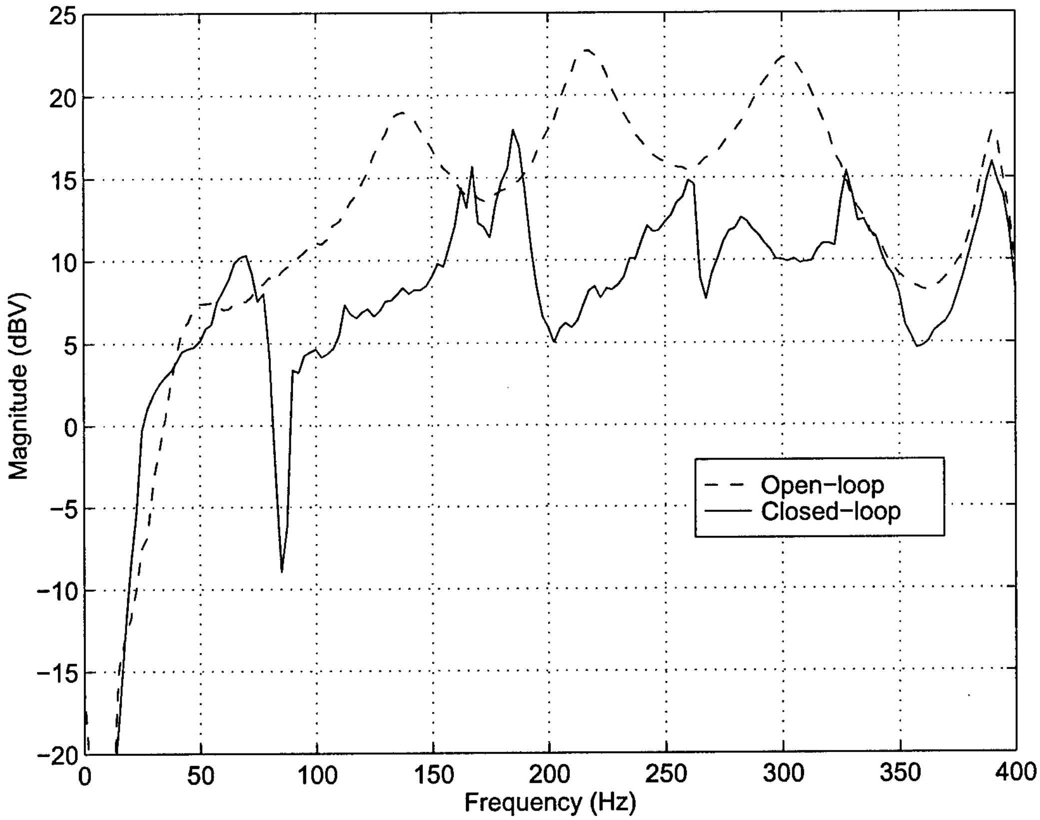

Figure 13: This frequency response plot compares the open- and closed-loop performance of the ARMarkov adaptive control algorithm with broadband disturbance.

6 Linear Systems and Control

A comprehensive study of guaranteed cost bounds for robust stability and performance analysis is given in [10]. Robust fixed-structure controllers formulated in the delta domain are considered in [15].

Vibration analysis of coupled oscillators is treated in [6], while reversible linear systems are characterized in [7]. These results contribute a systems theory foundation for thermodynamics, with application to active vibration control.

7 Nonlinear Control

Nonlinear control methods were developed for spacecraft control with shape change actuation. These methods use changes to the spacecraft configuration to enable attitude control. Controllers were implemented on a laboratory testbed involving single-degree-of-freedom motion and moving-mass actuation [9]. The laboratory testbed is shown in Figure 15. Extensions to 3-dimensional attitude control are studied in [40].

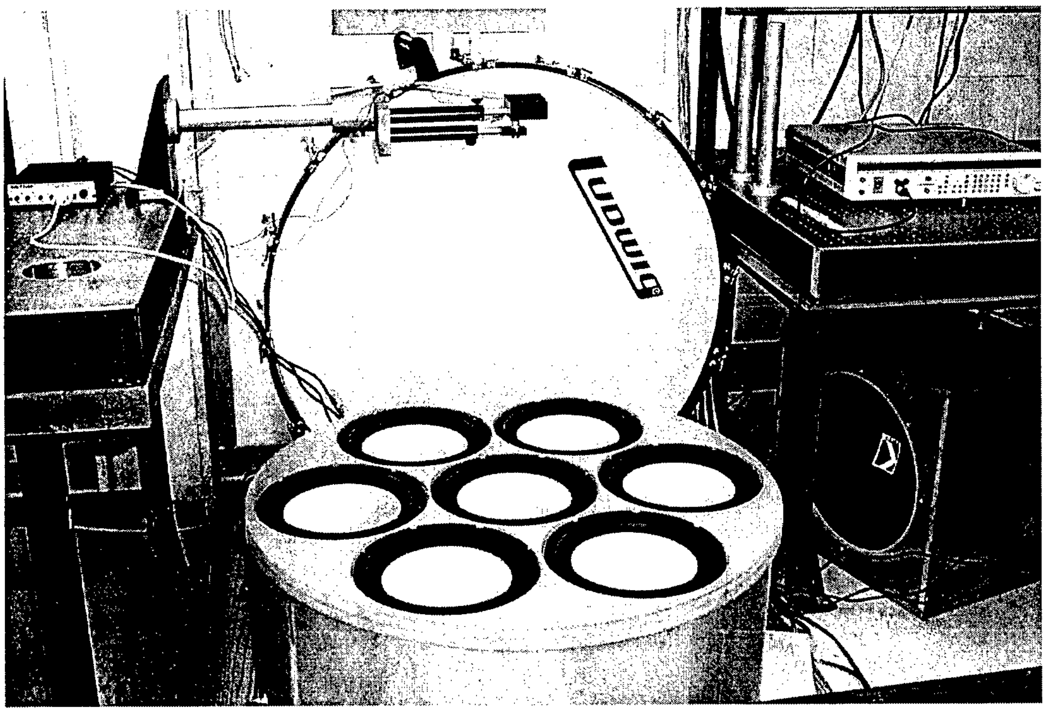

Figure 14: Membrane control experiment. A commercial bass drum provides a flexible membrane for adaptive disturbance rejection experiments. An array of seven audio speakers is mounted beneath the membrane for excitation, while a laser and optical sensor are used to measure surface slope deflection.

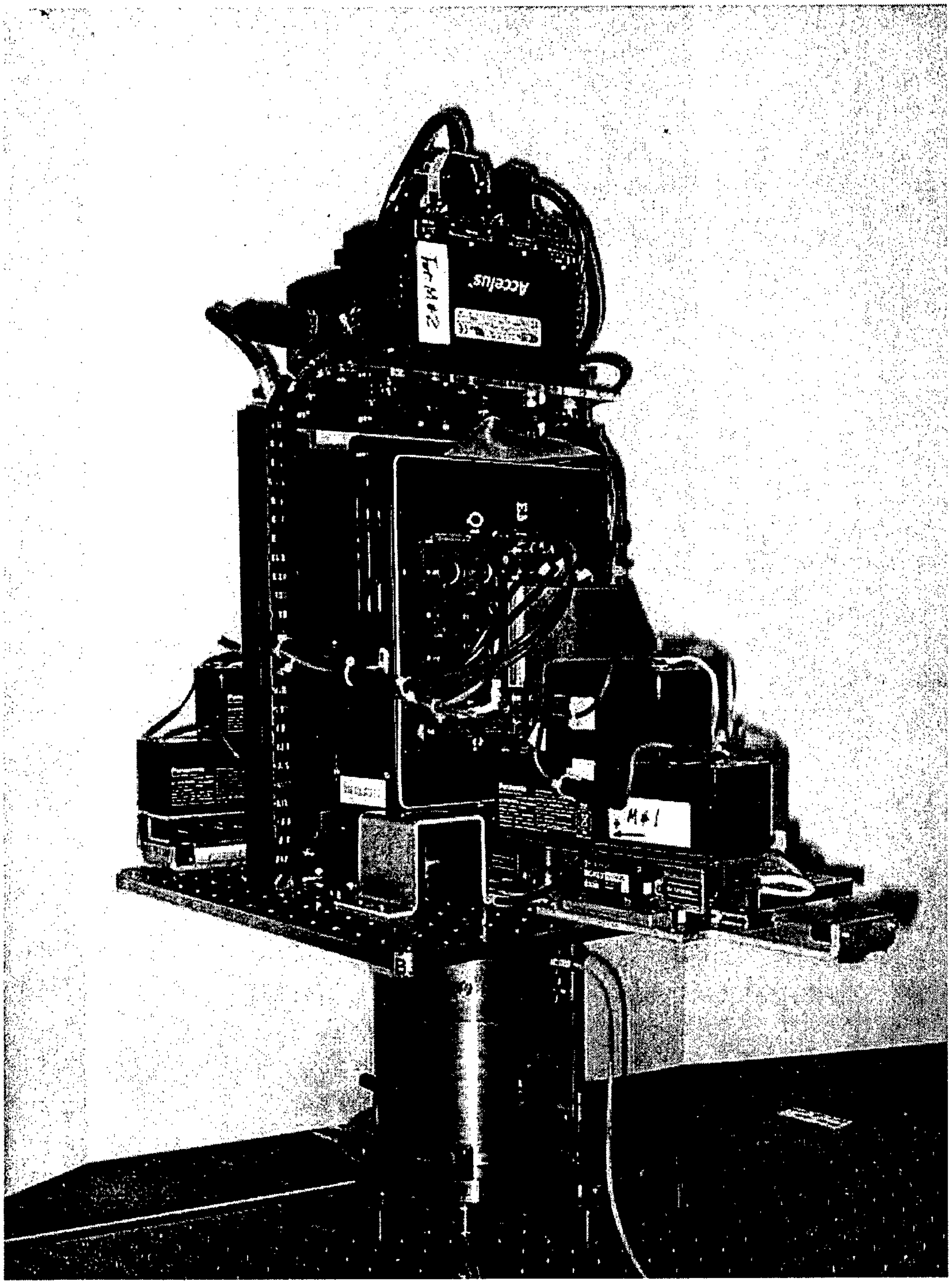

Figure 15: Shape change actuation experiment. An air bearing allows frictionless motion about a single axis for attitude control experiments. A pair of moving-mass actuators is used for shape change actuation. Several nonlinear control algorithms were implemented on the tested.

To support research in adaptive control, we developed the theory of semistability, which applies to systems with a continuum of equilibrium. This property is relevant to adaptive control systems, where parameter estimates need not converge to the true parameter values. Arc length tests for convergence were developed in [12], while nontangency tests are developed in [13].

Nonlinear controllers for finite-time stability were developed in [11].

8 Personnel

The research under this grant involved several current and former graduate students in the Aerospace Engineering Department of the University of Michigan supervised by the Principal Investigator. Although some of these students were supported under the prior grant, their research results were published within the time frame of the present project. These graduate students include Jasim Ahmed (currently at Bosch, Inc.), Suhail Akhtar (currently at the University of Michigan), Sanjay Bhat (currently at IIT Bombay), Jaganath Chandrasekar (currently at the University of Michigan), Scot Erwin (currently at AFRL/VS), Jesse Hoagg (currently at the University of Michigan), Seth Lacy (currently at AFRL/VS), Jin Oh (currently at the University of Michigan), Scot Osburn (currently at Aerospace Corp.), Harish Palanthandalam-Madapusi (currently at the University of Michigan), Alexander Roup (currently at Vehicle Control Technologies, Inc.), Jinglai Shen (currrently at RPI), Tobin Van Pelt (currently at Lockheed Martin), and Ravinder Venugopal (currently at Sysendes, Inc., Montreal). Professor N. Harris McClamroch was a major contributor to several aspects of this work.

9 Presentations

In addition to the presentations of conference papers as listed in the bibliography, aspects of this research were presented at Aerospace Corporation, AFRL/VS, Boeing, Ford, Honeywell Tech Center, Honeywell Corporation (Pheonix), JPL, NASA Dryden, Philips Corporation, Technical University of Delft, University of Glasgow, University of Illinois, University of Patras, and University of Strathclyde.

10 Acknowledgments

I wish to thank Marc Jacobs, Belinda King, and Sharon Heise of AFOSR/NM for their generous support of this research.

References

[1] J. Ahmed and D. S. Bernstein. Adaptive Control of a Double-Gimbal Control-Moment Gyro with Unbalanced Rotor. *AIAA J. Guid. Contr. Dyn.*, 25:105–115, 2002.

[2] J. Ahmed, V. T. Coppola, and D. S. Bernstein. Asymptotic Tracking of Spacecraft Attitude Motion with Inertia Identification. *AIAA J. Guid. Contr. Dyn.*, 21:684–691, 1998.

[3] S. Akhtar and D. S. Bernstein. Lyapunov-Stable Discrete-Time Model Reference Adaptive Control. In *Proc. Amer. Contr. Conf.*, Boston, MA, June 2004.

[4] S. Akhtar, R. Venugopal, and D. S. Bernstein. Discrete-Time Direct Adaptive Stabilization. In *Proc. Amer. Contr. Conf.*, pages 214–219, Denver, CO, June 2003.

[5] S. Akhtar, R. Venugopal, and D. S. Bernstein. Logarithmic Lyapunov Functions for direct Adaptive Stabilization with Normalized Adaptive Laws. *Int. J. Contr.*, to appear.

[6] D. S. Bernstein and S. P. Bhat. Energy Equipartition and the Emergence of Damping in Lossless Systems. In *Proc. Conf. Dec. Contr.*, pages 2913–2918, Las Vegas, NV, December 2002.

[7] D. S. Bernstein and S. P. Bhat. Linear Output-Reversible Systems. In *Proc. Amer. Contr. Conf.*, pages 3240–3241, Denver, CO, June 2003.

[8] D. S. Bernstein, N. H. McClamroch, and J. Shen. An Air Spindle Testbed for Experimental Investigation of Shape Change Actuation for Precision Attitude Control. *Contr. Sys. Mag.* to appear.

[9] D. S. Bernstein, N. H. McClamroch, and J. Shen. An Air Spindle Testbed for Experimental Investigation of Shape Change Actuation for Precision Attitude Control. *IEEE Contr. Sys. Mag.*, 23(October):44–56, 2003.

[10] D. S. Bernstein and S. L. Osburn. Guaranteed Cost Inequalities for Robust Stability and Performance Analysis. *Int. J. Robust Nonlinear Contr.*, 12:1275–12977, 2002.

[11] S. P. Bhat and D. S. Bernstein. Finite-Time Stability of Homogeneous Systems. In *Proc. Amer. Contr. Conf.*, pages 2513–2514, Albuquerque, NM, June 1997.

[12] S. P. Bhat and D. S. Bernstein. Arc-Length-Based Lyapunov Tests for Convergence and Stability in Systems Having a Continuum of Equilibria. In *Proc. Amer. Contr. Conf.*, pages 2961–2966, Denver, CO, June 2003.

[13] S. P. Bhat and D. S. Bernstein. Nontangency-Based Lyapunov Tests for Convergence and Stability in Systems Having a Continuum of Equilibria. *SIAM J. Contr. Optim.*, 42:1745–1775, 2003.

[14] J. Chandresekar, L. Liu, D. Patt, P. P. Friedmann, and D. S. Bernstein. Adaptive Harmonic Steady State Control for Disturbance Rejection. In *Proc. Amer. Contr. Conf.*, Boston, MA, June 2004.

[15] R. S. Erwin and D. S. Bernstein. Fixed-Structure Discrete-Time Mixed H_2/H_∞ Controller Synthesis Using the Delta-Operator. *Int. J. Contr.*, 75:559–571, 2002.

[16] J. Hoagg and D. S. Bernstein. Direct Adaptive Stabilization of Minimum Phase Systems with Bounded Relative Degree. In *Proc. Amer. Contr. Conf.*, Boston, MA, June 2004.

[17] J. B. Hoagg, S. L. Lacy, R. S. Erwin, and D. S. Bernstein. Subspace Identification with Lower Bounded Modal Frequencies. In *Proc. Amer. Contr. Conf.*, Boston, MA, June 2004.

[18] J. B. Hoagg, R. Venugopal, S. L. Lacy, and D. S. Bernstein. Adaptive Control of a Flexible Membrane Using Acoustic Excitation and Optical Sensing. In *AIAA Guid. Nav. Contr. Conf.*, Austin, TX, August 2003. submitted.

[19] J. Hong and D. S. Bernstein. Experimental Application of Direct Adaptive Control Laws for Adaptive Stabilization and Command Following. In *IEEE Conf. Dec. Contr.*, pages 779–783, Phoenix, AZ, December 1999.

[20] J. Hong and D. S. Bernstein. Adaptive Stabilization of Nonlinear Oscillators Using Direct Adaptive Control. *Int. J. Contr.*, 74:432–444, 2001.

[21] S. Lacy, D. S. Bernstein, and R. S. Erwin. Finite-Horizon Input Selection for System Identification. In *Proc. Contr. Dec. Conf.*, pages 6485–6490, Maui, HI, December 2003.

[22] S. L. Lacy and D. S. Bernstein. Subspace Identification for Nonlinear Systems That are Linear in Unmeasured States. In *Proc. Conf. Dec. Contr.*, pages 3518–3523, Orlando, FL, December 2001.

[23] S. L. Lacy and D. S. Bernstein. Identification of an Electromagnetic Actuator. In *Proc. Conf. Dec. Contr.*, pages 4521–4526, Las Vegas, NV, December 2002.

[24] S. L. Lacy and D. S. Bernstein. Identification of an Electromagnetic Actuator. In *Proc. Conf. Dec. Contr.*, pages 4521–4526, Las Vegas, NV, December 2002.

[25] S. L. Lacy and D. S. Bernstein. Identification of FIR Wiener Systems with Unknown, Noninvertible, Polynomial Nonlinearities. *Int. J. Contr.*, 76:1500–1507, 2003.

[26] S. L. Lacy and D. S. Bernstein. Identification of Systems with Limit Cycles. In *Proc. Amer. Contr. Conf.*, pages 3863–3868, Denver, CO, June 2003.

[27] S. L. Lacy and D. S. Bernstein. Subspace Identification with Guaranteed Stability Using Constrained Optimization. *IEEE Trans. Autom. Contr.*, 48:1259–1263, 2003.

[28] S. L. Lacy, R. S. Erwin, and D. S. Bernstein. Identification of Wiener Systems with Known Noninvertible Nonlinearities. *J. Dyn. Sys. Meas. Contr.*, 123:566–571, December 2001.

[29] J. Oh and D. S. Bernstein. A Semilinear Duhem Model for Rate-Independent Hysteresis. In *Proc. Contr. Dec. Conf.*, pages 6236–6241, Maui, HI, December 2003.

[30] J. Oh and D. S. Bernstein. Identification of Rate-Dependent Hysteresis Using the Semilinear Duhem Model. In *Proc. Amer. Contr. Conf.*, Boston, MA, June 2004.

[31] H. Palanthandalam-Madapusi, J. B. Hoagg, and D. S. Bernstein. Basis-Function Optimization for Subspace-Based Nonlinear Identification of Systems with Measured-Input Nonlinearities. In *Proc. Amer. Contr. Conf.*, Boston, MA, June 2004.

[32] T. H. Van Pelt and D. S. Bernstein. Nonlinear System Identification Using Hammerstein and Nonlinear Feedback Models with Piecewise Linear Static Maps. *Int. J. Contr.*, 74:1807–1823, 2001.

[33] T. H. Van Pelt and D. S. Bernstein. Quadratically Constrained Least Squares Identification. In *Proc. Amer. Contr. Conf.*, pages 3684–3689, Arlington, VA, June 2001.

[34] A. Roup and D. S. Bernstein. Adaptive Stabilization of Second-Order Systems with Bounded Time-Varying Coefficients. In *Proc. Conf. Dec. Contr.*, pages 3471–3472, Orlando, FL, December 2001.

[35] A. V. Roup and D. S. Bernstein. Stabilization of a Class of Nonlinear Systems Using Direct Adaptive Control. *IEEE Trans. Autom. Contr.*, 46:1821–1825, 2001.

[36] H. Sane and D. S. Bernstein. Asymptotic Disturbance Rejection for Hammerstein Positive Real Systems. *IEEE Trans. Contr. Sys. Tech.*, 11:364–374, 2003.

[37] A. Sanyal, M. Chellapa, J. L. Valk, J. Shen, J. Ahmed, and D. S. Bernstein. Globally Convergent Adaptive Tracking of Spacecraft Angular Velocity with Inertia Identification. In *Proc. Contr. Dec. Conf.*, pages 2704–2709, Maui, HI, December 2003.

[38] A. K. Sanyal, M. Chellapa, J. L. Valk, J. Ahmed, and D. S. Bernstein. Globally Convergent Adaptive Tracking of Spacecraft Angular Velocity with Inertia Identification. In *Proc. SYSID 2003*, Rotterdam, August 2003.

[39] J. Shen, N. H. McClamroch, and D. S. Bernstein. Air Spindle Attitude Control via Proof Mass Actuators. In *Proc. Conf. Dec. Contr.*, pages 4616–4621, Orlando, FL, December 2001.

[40] J. Shen, N. H. McClamroch, and D. S. Bernstein. Air Spindle Attitude Control via Proof Mass Actuators. In *Proc. Conf. Dec. Contr.*, pages 4616–4621, Orlando, FL, December 2001.

[41] J. Shen, N. H. McClamroch, and D. S. Bernstein. Attitude Control of a Tilted Air Spindle Testbed Using Proof Mass Actuators. In *Proc. Amer. Contr. Conf.*, pages 934–939, Anchorage, AK, May 2002.

[42] R. Venugopal and D. S. Bernstein. Adaptive Disturbance Rejection Using ARMARKOV System Representations. *IEEE Trans. Contr. Sys. Tech.*, 8, 2000.

[43] R. Venugopal and D. S. Bernstein. Noise and Vibration Suppression Method and System. *United States Patent 6,208,739*, March 27, 2001.

[44] R. Venugopal, V. G. Rao, and D. S. Bernstein. Lyapunov-Based Backward-Horizon Discrete-Time Adaptive Control. *Adaptive Contr. Sig. Proc.*, 17:67–84, 2003.